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Rice yield in response to climate trends and drought index in the Mun River Basin, Thailand

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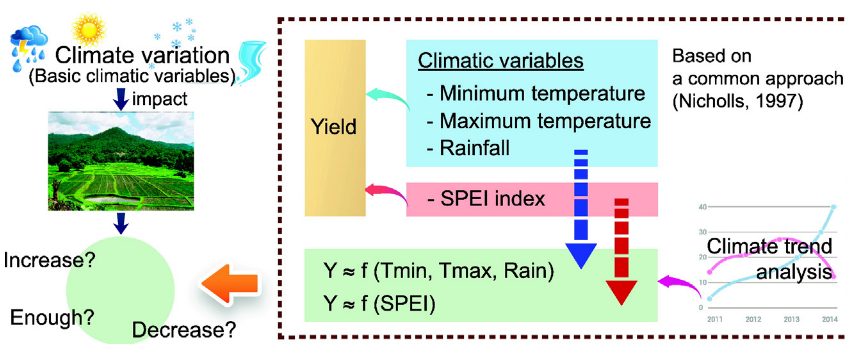
HIGHLIGHTS

- Analysis of impacts of past climate trends on rice yield in the Mun River Basin.
- The analysis also includes relationships between rice yield and SPEI.
- Increasing Tmax and Tmin cause damage to rice production in the area.
- 1-month SPEI has stronger relationship with rice yield than other timescales and rainfall.
- The rice yield impacts due to climate trends in the basin were rather low.

GRAPHICAL ABSTRACT



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ABSTRACT

Rice yields in Thailand are among the lowest in Asia. In northeast Thailand where about 90% of rice cultivation is rain-fed, climate variability and change affect rice yields. Understanding climate characteristics and their impacts on the rice yield is important for establishing proper adaptation and mitigation measures to enhance productivity. In this paper, we investigate climatic conditions of the past 30 years (1984–2013) and assess the impacts of the recent climate trends on rice yields in the Mun River Basin in northeast Thailand. We also analyze the relationship between rice yield and a drought indicator (Standardized Precipitation and Evapotranspiration Index, SPEI), and the impact of SPEI trends on the yield. Our results indicate that the total yield losses due to past climate trends are rather low, in the range of <50 kg/ha per decade (3% of actual average yields). In general, increasing trends in minimum and maximum temperatures lead to modest yield losses. In contrast, precipitation and SPEI-1, i.e. SPEI based on one monthly data, show positive correlations with yields in all months, except in the wettest month (September). If increasing trends of temperatures during the growing season persist, a likely climate change scenario, there is high possibility that the yield losses will become more serious in future. In this paper, we show that the drought index SPEI-1 detects soil moisture deficiency and crop stress in rice better than precipitation or precipitation based indicators. Further, our results emphasize the importance of spatial and temporal resolutions in detecting climate trends and impacts on yields.

1. Introduction

Temperature and precipitation are the two fundamental variables commonly used as indicators for changes in climate. The impacts of climate variability and change on crop yields have been studies by

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numerous researchers worldwide; both for historical and future climates and for various crops (Adams et al., 1998; Babel et al., 2011; Bhatt et al., 2014; Challinor et al., 2014 etc.; Erda et al., 2005; Fischer et al., 2005; Fuhrer et al., 2006; Hekstra, 1986; Nicholls, 1997). Studies on the impacts of past climate trends on crop yields using empirical models have come to different conclusions depending on crop types and their locations. For example, some studies reported reductions in wheat yields in Russia and France, and maize yields in China as a result of increased temperature (Brisson et al., 2010; Lobell et al., 2011; Tao et al., 2008; Wei et al., 2014). Others report increases in wheat yields in Mexico due to decreased nighttime temperature (Lobell et al., 2005), whereas an increase in minimum temperature is the dominant factor attributed to increases Australian wheat yields (Nicholls, 1997). Furthermore, rice yields in China have increased due to significant warming trend (Tao et al., 2008). In the United States, the yield impacts on wheat, maize and soybean are not obvious because of less significant climate trends (Lobell et al., 2011). In a study in the Koshi basin (Nepal) Bhatt et al. (2014) pointed out that crop yield impacts differ even in the same basin depending on altitudes.

These findings have resulted in an improved understanding of the links between climate and crop yields and the extent to which climate impacts productivity. However, these studies used basic climatic variables such as minimum, maximum and mean temperatures and precipitation at a rather coarse temporal (annual or by growing season) and spatial scale, such as global (Lobell and Field, 2007; Lobell et al., 2011), regional (Lobell et al., 2007; Schlenker and Lobell, 2010), and national scale (Nicholls, 1997; Rowhani et al., 2011; Wei et al., 2014).

Drought indices relate to cumulative effects of a prolonged and abnormal moisture deficiency (World Meteorological Organization, 1992), thus they have a strong connection to agriculture. There are a number of drought indices commonly used such as Standardized Precipitation Index (SPI) (McKee et al., 1993), Standardized Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), Palmer Drought Severity Index (PDSI) (Palmer, 1965), Normalized Difference Vegetation Index (NDVI) (Tucker, 1979).

The SPEI, a meteorological drought index, is more relevant to agriculture than precipitation or precipitation-based indices such as SPI, because it is based on both precipitation and temperature. It can be computed at any preferable timescales and the values represent both wet and dry conditions (Guttman, 1999; Zargar et al., 2011). which both can affect crop yields when threshold values are exceeded. In addition, the meteorological drought index can detect the onset of drought sooner than agricultural and hydrological drought indices. However, even though SPEI has been widely used for monitoring and forecasting climate variations and conditions, it is rarely used to evaluate the link between crop yields and climate.

The objectives of this paper are to examine climate variability and trends, and the relationships between rice yields and basic climatic parameters such as minimum (Tmin), average (Tave), maximum (Tmax) temperatures, precipitation (Prec), and the drought index SPEI. This study is implemented for the Mun River Basin, Thailand, where no such study has been executed before. The study advances previous work by assessing yield changes at monthly time step rather than using averages or summations over the growing season. A shorter time step is important because of the varying degree of crop sensitivity to climate at each growth stage. In addition, this study takes a finer spatial scale than earlier studies, using basin and sub-basin scales as opposed to national level and global assessments. Because the climate - yield relationship is scale dependent and empirical models at global scale cannot reliably be used to anticipate the outcomes at finer scales (Lobell and Field, 2007; Tao et al., 2008), assessments on a smaller spatial scale (such as basin level) deepens the understanding of crop-climate links.

2. Study area

Thailand is among top ten largest rice-producing countries in the world (FAO, 2013), but its annual average rice yield of 3.1 ton/ha is only half of rice yields in South Korea and Japan and ranks almost at the bottom among the Southeast Asian countries (Food and Agriculture Organization of the United Nations, 2016). The lowest average yield in Thailand, 2.3 ton/ha, is found in the northeastern region where approximately 60% of rice is cultivated (Office of Agricultural Economics, 2016).

The Mun River Basin, the largest river basin in Thailand with a total area of 71,060 km^2 is located in the northeast of the country, covering 10 provinces (Fig. 1). It has a tropical savannah climate (Peel et al., 2007), with an annual precipitation between 800 mm and 1800 mm concentrated in the rainy season from mid-May to mid-October, with maxima in August or September. The monthly mean temperature ranges from 25 °C to 30 °C. In the cool season, i.e., mid-October to mid-February, not only the temperature but also the precipitation is lowest. The hot period is from mid-February to mid-May, with the highest temperature in April.

Approximately 75% of total agricultural land in the Mun River Basin (5.2 million ha) is devoted to paddy fields of which about 90% is rain-fed (Table 1). The total rice cultivation and irrigated areas were derived from the land use map of 2013 obtained from the Land Development, Thailand and the map of irrigated area 2012–2013 obtained from the Royal Irrigation Department, Thailand. The KDML105 (Khao Dok Mali 105) and RD6 (Rice Department 6) are the two main varieties of Jasmine rice in the area with a potential yield of 2.3 t/ha and 4.2 t/ha respectively. They are medium-maturing types with a life cycle of 120–140 days, roughly from July to November (Bureau of Rice Research and Development (BRRD), n.d.). The common technique for rice cultivation in Thailand nowadays is direct seeding. The three development stages (Brouwer et al., 1989) are the vegetative stage (July–September), reproductive stage (October) and ripening stage (November).

Rainfed rice yields in the Mun River basin are generally below potential due to water shortages. The average total precipitation over rice-growing season varies between 600 and 1100 mm (average 821 mm) with considerable spatial and temporal variations from province to province as shown in Fig. 1. The eastern provinces receive more precipitation than the west because of the influence of tropical depressions (The Meteorological Department of Thailand, n.d.). The amount of precipitation decreases considerably after the rainy season. The precipitation concentrates in the months July to September (200 mm per month or more). The last two months of the growing season (October and November) are relatively dry. The effective precipitation is approximately 550 mm (Table 2). This amount is not sufficient for rice cultivation, which requires roughly 1300–1600 mm (including the amount of water needed for soil saturation, percolation, seepage losses and water layer establishment). The predominant soil types consist of coarse-loamy, fine-silty, fine-loamy, clayey-skeletal soils with average percolation and seepage losses up to 5 mm/day.

3. Data and methods

3.1. Data collection

Time series data of monthly precipitation, Tmin and Tmax from 1984 to 2013 were obtained from the Royal Irrigation Department and the Meteorological Department of Thailand. Of the total 196 precipitation stations in the basin, only 53 have continuous time-series records for the specified period. Among them, only 10 stations also have adequate temperature data. Therefore, data from several adjacent stations outside the basin were included. Annual rice production data of the 10 provinces were acquired from the Office of Agricultural Economics, Ministry of Agriculture and Cooperatives. The length of the yield records

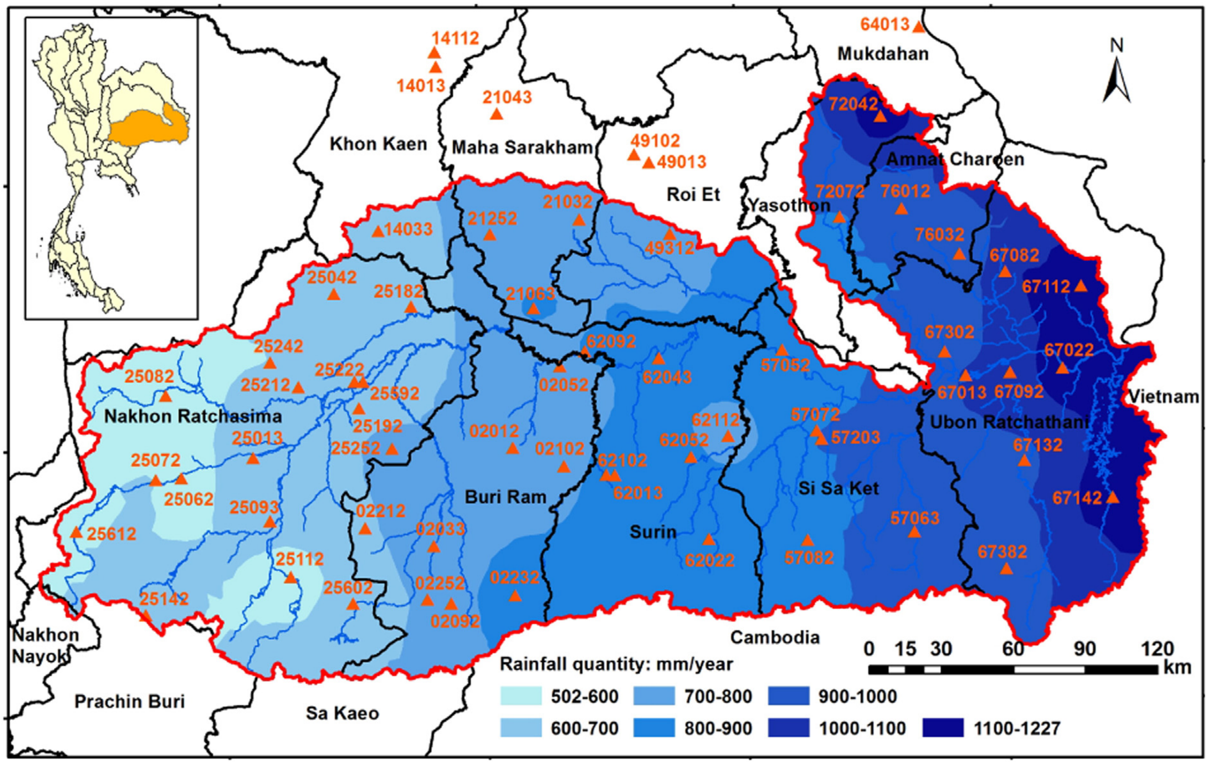

Fig. 1. Spatial distribution map of average total precipitation during rice-growing season at the Mun River Basin, Thailand for 1984–2013 created from 61 meteorological stations (triangle) selected for the study. The basin boundary (red line) covers 10 provinces (black line).

corresponds with the length of climatic records, except for the Amnat Charoen province where the recording of data only started in 1994.

3.2. Drought index calculation and classification

The SPEI is based on monthly differences between precipitation and potential evapotranspiration (PET). There are different methods to compute PET varying from simple methods, such as Thornthwaite (1948) or Hargreaves (1994), to sophisticate ones, such as Penman-Monteith (PM) (Allen et al., 1998). Though the PM method has been accepted as the standard method by the Food and Agriculture Organization of the United Nations (FAO), the International Commission for Irrigation and Drainage (ICID) and the World Meteorological Organization (WMO), here we choose the Hargreaves method because of data limitations. Moreover, Mavromatis (2007) concluded that for the computation of drought indices, simple PET estimation methods provide outcomes similar to the complex methods. Beguería et al. (2014) compared the SPEI values calculated with three different PET estimation methods: Penman-Manteith, Hargreaves, and Thornthwaite. They found that the differences are small in humid regions and recommended the Hargreaves equation over the Thornthwaite equation in data scarce areas.

Water deficit or surplus for a specific month i is calculate using:

$$D_i = P_i - PET_i \tag{1}$$

where D_i is the water deficit or surplus at month i (mm/month), and P_i is effective precipitation (mm/month).

The D_i values were aggregated at different time scales, following the same procedure as that for the SPI. The log-logistic distribution was used to standardize the D series to derive the SPEI values at preferred time scales. The SPEI at 1- and 3-month timescales were considered because they are relevant to agriculture (Potop et al., 2014). Monthly SPEIs of each province over 30 years were determined, but only the months of the rice-growing season (July to November) were used in further analysis.

Following previous studies (Santiago Beguería et al., 2014; Dorman et al., 2015; Wang et al., 2015), the R package was used to compute PET and SPEI, developed by S Beguería and Vicente-Serrano (2013). The classification of droughts using the SPEI values given in Table 3 follows the same criteria as the SPI due to their similarity in fundamental principles and calculation (Tan et al., 2015).

Table 1
Irrigated rice fields by province in the Mun River Basin.

Province	Rice area (km^2)	Irrigated area (km^2)	% Irrigated area
Nakhon Ratchasima (Na)	6479	1260	19.4%
Buri Ram (Bu)	6032	472	7.8%
Khon Kaen (Kh)	749	4	0.5%
Maha Sarakham (Ma)	1872	94	5.0%
Surin (Su)	5933	298	5.0%
Roi Et (Ro)	2517	174	6.9%
Si Sa Ket (Si)	5437	271	5.0%
Yasothon (Ya)	1401	69	4.9%
Amnat Charoen (Am)	1659	79	4.8%
Ubon Ratchathani (Ub)	6482	381	5.9%
Total	38,561	3102	8.0%

Provinces are listed from West to East.

Table 2
Average monthly precipitation and effective precipitation (mm) for rice-growing season from 1984 to 2013.

	Jul	Aug	Sep	Oct	Nov	Total
Average precipitation	196	242	250	113	20	821
Effective precipitation[a]	132	169	175	65	2	543

[a] That part of the precipitation that is stored in the root zone and can be used by crops, calculated based on Brouwer et al. (1989).

Table 3
Dry/wet conditions corresponding with the seven SPEI categories.
Source: Potop et al. (2014).

SPEI value	Category
≥2.00	Extreme wet (EW)
1.50 to 1.99	Severe wet (SW)
1.49 to 1.00	Moderate wet (MW)
0.99 to −0.99	Normal (N)
−1.00 to −1.49	Moderate drought (MD)
−1.50 to −1.99	Severe drought (SD)
≤−2.00	Extreme drought (ED)

3.3. Correlation, relationship and impact analysis

Correlations of rice yield with climatic variables were estimated following an established approach as described in (Bhatt et al., 2014; Lobell and Field, 2007; Lobell et al., 2005; Nicholls, 1997). This approach removes confounding effects of long-term variations in yields, such as cultivars, crop management and fertilizers, by calculating the first differences in the yield, climatic variables and drought index ($VAR_t - VAR_{t-1}$). In the next step, the Pearson product-moment correlation coefficients were calculated. The correlation results provide initial information on the positive or negative sign of relationships which helps understanding the regression results.

Subsequently, the relationships of rice yield with the climate variables and with the SPEIs were investigated using a multiple linear regression model. Though less complex than crop simulation models, the multiple linear regression model is able to capture the net climate effects of combined climate variables at monthly time steps during the growing season (Lobell and Field, 2007). The intercept was forced through zero to avoid trend effects (Nicholls, 1997). The multivariate linear regression is of the form:

$$\Delta Y_i = \gamma_{1i}{}^{*}\Delta Tmin + \gamma_{2i}{}^{*}\Delta Tmax + \gamma_{3i}{}^{*}\Delta Prec \quad (2)$$

where ΔY_i is first differences in annual rice yield of province i (t/ha), $\Delta Tmin$ and $\Delta Tmax$ are first differences in minimum and maximum temperatures (°C), $\Delta Prec$ is first differences in precipitation (mm), and γ is a vector of estimated coefficients. Similarly, the approach was applied to the SPEIs as following:

$$\Delta Y_i = \alpha_{1i}{}^{*}\Delta SPEI \quad (3)$$

where $\Delta SPEI$ is first differences in SPEI values and α is a vector of estimated coefficient.

Bootstrapping technique (Fox, 2015; Lobell and Field, 2007) was employed to overcome size limitation of the 30 years timeseries data by resampling 1000 bootstrap samples (independent random sample). By re-calibrating estimated coefficients, this technique provides more precise statistical inferences of the coefficients, including their relevant 90% confident intervals.

After running the regression and determining the regression coefficients, the first differences values were substituted by the trend slopes of climatic variables and of SPEI. This provide the impact of climate trends on crop yields. Because climatic trends affect crop development in different growth stages differently, the analysis was carried out not only for the average values over rice-growing season, but also for each individual month of the growing period.

4. Results

4.1. Observed temporal variations of wet and dry conditions

The analysis of the SPEI indicates that over the past 30 years the basin encountered both extreme wet and extreme dry conditions (Fig. 2). The dry/wet conditions as indicated by the 1-month SPEI (SPEI-1) changed more frequently than shown by the 3-month timescales because the SPEI-1 values represent the conditions of each individual month, and thus the influence of dry/wet conditions does not affect the next consecutive month. On the other hand, in the computation of the SPEI-3, extreme weather conditions of one month are visible in SPEI values of the next two consecutive months. This makes the duration of extreme events as indicated by the SPEI-3 longer than as shown by SPEI-1.

During the months of the rice-growing season, all dry and wet conditions occurred (Table 4). Approximately 35% of the total number of months experienced anomalous dry or wet conditions. The proportion of wet months was slightly higher than the dry ones. The number of extreme wet and dry months increased considerably when the time scale increased from 1 month to 3 months (i.e. SPEI-1 to SPEI-3). This shows that extreme events may not always be detected effectively with the 1-month SPEI because impacts accumulate and become more visible over time. Therefore, the SPEI-1 in combination with *SPE*I-3 provide a more complete description of dry/wet conditions.

The SPEI-1 values, which represent short-term soil moisture and crop stress during the growing season (The National Drought Mitigation Center (NDMC), n.d.), fluctuate remarkably from one month to another. For example, in Khon Kaen province, severe drought in October 2002 was followed by an extreme wet month, and in the Amnat Charoen province, a severe wet July in 2013 changed to severe drought in August. Such quick variations in weather conditions were rare before the year 2000, but became more frequently afterwards (Table 5).

The SPEI-3 values, which represent seasonal conditions (The National Drought Mitigation Center (NDMC), n.d.) indicate that dry conditions of different categories were more prominent in the period 1986–1999, whereas wet conditions were more prominent in the period after 1999 (Fig. 3). Another interesting observation is the alternate occurrences of floods and droughts in recent years. For example, high

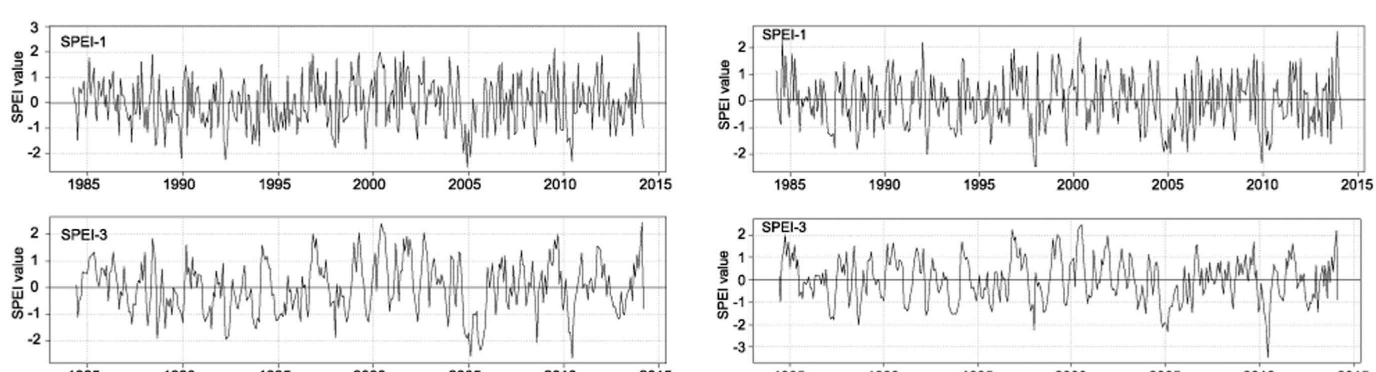

Fig. 2. Examples of temporal variations of SPEI values at 1- and 3- month timescales of Si Sa Ket province (left) and Ubon Ratchathani province (right) for 1984–2013.

Table 4
Number of months during rice-growing period at different SPEI classifications of all ten provinces at 1- and 3-month timescales.

Category	SPEI-1	SPEI-3
Extreme wet (EW)	18	26
Severe wet (SW)	91	90
Moderate wet (MW)	157	144
Normal (N)	985	983
Moderate dry (MD)	167	166
Severe dry (SD)	73	65
Extreme dry (ES)	9	26
Total wet	266	260
Total dry	249	257

precipitation in years 2001 (1380 mm) and 2002 (1400 mm) leading to floods were followed by the dry years in 2003 (1140 mm) and 2004 (1090 mm), and the great flood in 2011 (1460 mm) was followed by dry conditions in 2012 (1030 mm).

4.2. Observed climate trends

Trend analysis shows that climate variables and SPEI trends are mostly increasing (Table 6), in particular, those with a significant level of 90% or better (the Tmin trend in the Khon Kaen province in August is an exception). Tmin and Tmax exhibit the most significant increasing trends as compared to the other variables, with provinces in the East exhibiting clearer warming trends than in the West. Tmin has a more significant warming trend than Tmax. The significant trend values of Tmin vary between −0.1–0.65 °C per decade, distributed over all months. The month November exhibits the highest warming trend, ranging between 0.45 and 0.65 °C per decade. Lower warming rates are observed in the first three months of the growing season, with the lowest rates in August and September. Tmax shows an even higher upward trend with rates up to 0.8 °C per decade. The statistically significant increasing trends in Tmax occur mostly in October (0.3–0.6 °C per decade) and November (0.45–0.8 °C per decade). The statistically significant trends in precipitation and SPEI-1 are all increasing and concentrated in August and September, with increases in precipitation varying between 10 and 60 mm per decade and highest values occurring in the Maha Sarakham and Yasothon provinces. The SPEI-1 exhibits an increasing trend of 0.2–0.5 per decade.

4.3. Climate–rice yield correlations

4.3.1. Correlation rice yields with temperatures

Our results show that rice yields are generally negatively correlated with temperatures Tmin, Tmax and Tave (Table 7). The correlation of rice yield with Tmax, Tmin, and Tave are comparable and predominantly negative at the significance level 90% or higher (p-value ≤ 0.1), except for Tmin in the Ubon Ratchathani province in November (Table 8). Tmax exhibits a slightly stronger correlation with the rice yield than Tmin and Tave, which is in agreement with the findings of Bhatt et al. (2014). The strongest correlations with Tmin are found in November (the harvest month), especially in the eastern provinces, whereas the highest correlations with Tmax could be found in any month.

The mean of Tmin, Tmax and Tave over the growing season exhibit correlations comparable to those for individual months. The negative correlations in Jul, Oct and Nov dominate some of the positive correlations observed in Aug and Sep resulting in negative correlations with the seasonal mean in all provinces except Ub (Table 8). All the positive correlations observed with temperatures are however statistically insignificant at 90% or higher confidence level, except in Nov with Tmin in Ub province. The mean of Tmin values over the growing season exhibit significant correlations with yield in four provinces (Na, Kh, Ro and Ya), out of the total seven provinces where individual months show significant correlations with the yield (Na, Kh, Ro, Si, Ya, Am and Ub). For the mean Tmax this occurred in five (Na, Kh, Ro, Si and Ya) out of eight provinces (Na, Kh, Ma, Ro, Si, Ya, Am and Ub). This shows that mean temperature values over the growing season provide satisfactory results in the analysis as well as temperature values of individual months.

4.3.2. Correlation rice yields with precipitation

The correlations of rice yields with precipitation are predominantly positive, except in September, but are generally weaker than with temperatures (Table 8). The highest correlations can be found in any month, except November. In November (harvest month) the least amount of water is required and water shortage during the last 15 days will not affect yields. On the contrary, dry conditions will homogenize maturation and facilitate harvesting (Wopereis et al., 2008).

The summation of monthly precipitation over the growing season exhibit only one significant correlation with the yield, although several significant correlations are observed with individual months. Because of large fluctuations between months, average or summation of precipitation over the growing season is not representative. This shows the importance of monthly values as opposed to annual or seasonal aggregations or averages.

4.3.3. Correlation rice yields with drought index SPEI

Yields are stronger correlated with the SPEI-1 than with the monthly precipitation and SPEI-3. More months exhibit a significant correlation with SPEI-1 than with precipitation or SPEI-3 (Table 7). The correlations with the 1-month SPEI exhibit a similar pattern to those with precipitation but stronger. The rice yield in the provinces on the west, (Na, Bu, Kh, Ma, and Su) clearly correlated with the SPEI-1 in September, while the high correlations of eastern provinces were in most of the months, but not in September and November (Table 9).

4.4. Climate impacts on rice yield

4.4.1. Regression with climatic variables

The regression results show that changes in climatic variables (Tmin, Tmax and precipitation) could explain the variance in year-to-year rice yield changes from 22% to 37% (Table 10). The unexplained yield variance reveals the importance of variables disregarded in this analysis, such as changes in financial status or other conditions that affect field management practices, as well as data uncertainty.

The regression results for a particular month gives more explanatory power (R^2) than for the average over the entire growing season. Those particular months may coincide with crucial crop development stages that directly influence yields, such as, tillering from the second half of August to mid-September and panicle differentiation from mid-September to October. Further, regressions with Tmin and Tmax separately gave more satisfactory outcomes (higher R^2) than using the mean temperature (Tave).

The regression results confirmed that rice yields respond negatively to the increases in Tmin and Tmax. This is in line with the previous findings from the U.S. (Edmonds and Rosenberg, 2005), and at global scale (Lobell and Field, 2007). Rice yields are more susceptible to changes in Tmin than in Tmax. However, in some provinces contradictory effects occur between increases in nighttime (Tmin) and daytime (Tmax) temperatures.

The relationships between yield and SPEI-1 reveal higher R^2 values as compared to yield and precipitation (Table 10). In 8 out of 10 provinces, the relationship of yield with SPEI-1 was statistically significant as compared to 5 out of 10 provinces for precipitation. The SPEI-1 can explain the year-to-year variance in rice yield for 10% to 16%. The coefficients of both precipitation and 1-month SPEI have the same direction, mostly positive, except in September.

4.4.2. Impact of climate trends on rice yields

Overall, observed climate trends suppress rice yields in all provinces, except in the Su province where the yield increased by 70 kg/ha per

Table 5
Spatial and temporal variations of climatic characteristics of rice-growing months that are classified based on SPEI-1 values.

Year	Na					Bu					Kh					Ma					Su				
	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11
1984											MW														
1985		ED	MW			MW	SD					MD							MW						
1986			MD									MW	SD					MD					MD		
1987	SD	MD	MW		SW	MD	SD	MW		SW	MD		SW		MW			MW		MW	SD	SD	MW		
1988		MD		MW			MD						MD	SW			SD	SD	MW		SD	SD	SD		
1989			SD															SD					MD		
1990				MW					MW				MW								MW			MW	
1991	MD	MW					MW						SW				MW					MW			
1992						MD	MW							MD				MD							
1993					MD		MD			MD		MD		MD	SD				MD	MD		MD		MD	MD
1994	SD			MD	MD	ED			MD	MD	MD				MD	SD			MD		MD	MW			
1995	SW					EW						SW	MW	MD		SW									
1996					SW			MW	MW	SW			MD		SW	MD				SW	MD		MW		EW
1997			SD							MD			MD		MD		MD	MD		MD	SW				MD
1998					MW					SW	SD	SW				SD	MW				MD	MD			MW
1999		MD			MW		MD			SW		MD					MD					MD			MW
2000		SW					SW	SD		MD				SW							MW	EW			
2001			MD					MD					MW				MW	SW	EW	MW		MW		MW	MW
2002	SD	MW	MW			SD	SW	SW			SD	MW		SD	EW		SW	MW				MW	MW		
2003				MD	SD		MD	MW	MD	MD				SD	ED			MW	SD	ED	MD		MW		MD
2004				ED	MD	EW	MW		ED	MD	SW		MD	SD	SD	EW			SD	SD	MW		MD	ED	SD
2005					SW					MW					MW	MW			MD	SW				MD	MW
2006				MW	MD			MD		MD	SW								SW	MD	MW		MD	MW	
2007	MD			MW								MW		MW		MD			MW					MW	
2008			MW		MW			MW		MW	MD	MW		SW		MD	MW	MW		SW	MD				MW
2009							MD									MW		SW					MW		
2010	SW	SW		EW				SD	EW		SW	MW	MD				SW							SW	
2011	MW		MW						MW								SW	SW						EW	
2012		MD							MD												MD			MD	
2013	SW		SW	MW				SW	SW		MW	SD				MW							SW		

Year	Ro					Si					Ya					Am					Ub				
	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11	7	8	9	10	11
1984				MW		MD							MD		MW		SW		MW	MW		EW		SW	
1985	MW	SW			MW					MW							MW				MD				
1986			SD					MD					MD												
1987	MD	MD						MW		SW						MW	MW	MW							MW
1988		MD		MW			SD	MD	MW		SD		MD	SW		MD		MD	SW		SD	SD	MD		
1989														MW											
1990				SW		MW										MW									
1991				MW		MD										MD		MW				MW	MW		
1992													MD					MD							
1993	MD	MD	MD	MD	MD			SD		MD					MD				MD	MD	MD		MD	MD	MD
1994	SD			MD					MD	MD	MD					MD		MW	MD						
1995			MD		SW	MW							SD			MW	SD	SD				SD	MD		
1996	MD				MW			SW		SW	MD		SW		SW		MD	MW		MW			SW		SW
1997	MW				MD	MW				MD	MW		SD		SD			SD		MD	MW		MD		MD
1998										SW		MD									MD				SW
1999		SD			MW		SD					SD	MW			MW	SD	MW				SD			
2000	MW	MW				MW	SW								MD		MD			MD	MW		MD		
2001					SW		EW		MW	MW		EW		SW				SW						SW	MW
2002		MD	ED	MD				SW			MW	SW		MD			MW		MD		MW		MW		
2003	SD				SD				MD	MD				SD	SD			MW	MD	MD	SD			MD	MD
2004	EW							MD	SD		MW			SD	MD			MD	SD	MD			SD	SD	MD
2005									MD							MD			MD	SW			MD	SD	MW
2006		MW		SW	SD		SW		SW						MD						SW	MW		MW	
2007	MD			MW		MD	MW		MW		SD			SW					SW					MW	
2008		SD	MW		EW	SD		MW			SD	SD			EW	ED	MD	SW		SW	MD		MW		
2009	MW	SW	SW			EW	MD	MW		MD	EW		MW			SW					SW		SW	MD	MD
2010									SW			MW		MW					SW						
2011	MW		SW	MW		MD		MW	SW			SW	MW				SW	MW	MW			MW		MW	MD
2012									MD											MW				MD	MW
2013			SW				MD	SW			MW	SD	SW			SW	SD				MW	SD	SW		

The provinces are presented from west to east according to their geographical locations. The numbers at the top of the table indicate the months (July to November). The climatic events are classified into two main groups: the wetness (blue) and dryness (orange). The colour levels display the degree of conditions ranging from moderate to extreme.

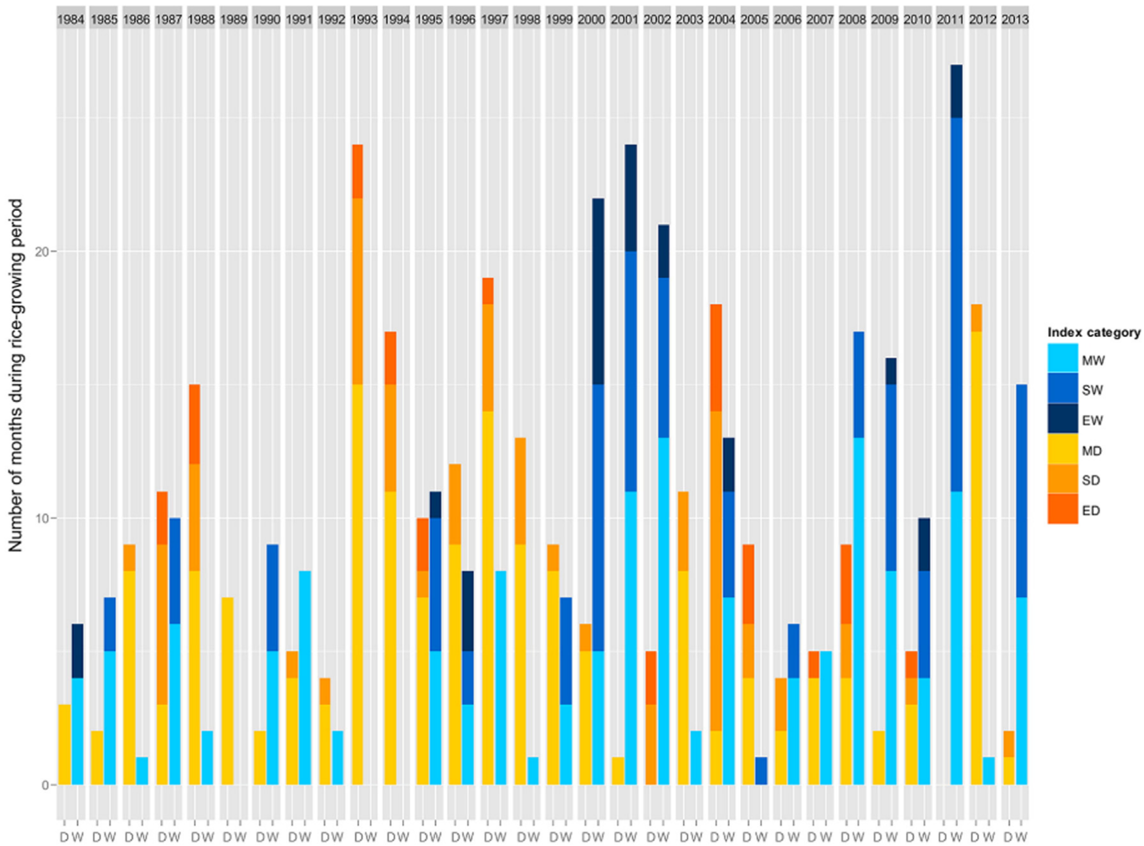

Fig. 3. Annual variations in the number of months affected by dry/wet conditions (SPEI ≤ −1 and SPEI ≥ 1) summed for all provinces from 1984 to 2013. The orange and blue colours present dry and wet conditions, respectively. Different shades of the colours define the intensities of dry (D) and wet (W) states. The classification is based on the SPEI-3 values.

decade (Fig. 4). The total yield losses of each province are mostly below 50 kg/ha (??? 3% compared to the average yield) per decade, driven by temperature trends rather than precipitation trends. In most cases, yields decline due to increasing trends of Tmin and Tmax. The reduction rate by province varied from 2 to 10% for each 1 °C increase in both Tmin and Tmax during the growing season.

Table 6
Trends in Tmin, Tmax, precipitation, and 1-month SPEI per decade for 1984–2013.

	Tmin						Tmax					
	7	8	9	10	11	Mean	7	8	9	10	11	Mean
Na	0.34***	0.30***	0.30***	0.47***	0.64**	0.41***	-0.06	-0.03	-0.13	0.26	0.47’	0.10
Bu	0.22**	0.24***	0.22**	0.23’	0.27	0.24**	0.06	0.13	0.04	0.34*	0.60*	0.23*
Kh	-0.01	-0.10*	0.05	0.13	0.28	0.07	0.06	-0.07	0.01	0.42*	0.50*	0.19’
Ma	-0.03	-0.08	0.09	0.27	0.47’	0.15	0.31*	0.09	0.22’	0.60**	0.78**	0.40**
Su	0.26**	0.20**	0.19**	0.25’	0.38	0.26**	0.12	0.09	0.05	0.38*	0.58*	0.24**
Ro	0.13	0.11*	0.22***	0.23	0.38	0.21**	0.18	0.08	0.06	0.38*	0.53*	0.24**
Si	0.28**	0.22**	0.20**	0.38*	0.47’	0.31***	0.17	0.10	-0.07	0.29*	0.45’	0.19*
Ya	0.28**	0.25***	0.29***	0.34*	0.52’	0.33***	0.39*	0.30**	0.30*	0.58**	0.77**	0.47***
Am	0.28**	0.25***	0.29***	0.34*	0.52’	0.33***	0.39*	0.30**	0.30*	0.58**	0.77**	0.47***
Ub	0.20’	0.16’	0.16’	0.19	0.46*	0.24*	0.28*	0.28**	0.11	0.58**	0.77**	0.41***

	Precipitation						SPEI1					
	7	8	9	10	11	Sum	7	8	9	10	11	Mean
Na	4.96	15.29’	16.70	9.64	0.53	9.42’	0.18	0.43*	0.36’	0.09	0.06	0.22*
Bu	5.68	19.02	12.10	10.78	1.04	9.73*	0.15	0.35’	0.16	0.13	-0.08	0.14
Kh	21.89	22.96	-5.83	5.35	1.18	6.08	0.23	0.17	-0.07	0.03	-0.20	0.06
Ma	21.33	36.06**	62.23*	-2.04	4.29	24.37**	0.21	0.45*	0.51*	-0.16	-0.08	0.19’
Su	14.88	25.01’	20.10	0.83	1.03	12.37*	0.22	0.36’	0.18	-0.06	-0.10	0.12
Ro	17.30	3.91	44.01’	-1.75	5.38	14.60	0.13	0.04	0.34	-0.06	-0.04	0.09
Si	23.58	2.07	27.18	-1.31	-6.68	8.97	0.22	0.01	0.28	-0.08	-0.16	0.06
Ya	38.53	9.71	65.04*	-3.34	1.52	22.29’	0.27	-0.08	0.50*	-0.14	-0.20	0.07
Am	15.23	-23.78	22.17	-8.46	3.04	1.64	0.18	-0.23	0.20	-0.25	-0.12	-0.04
Ub	25.63	-19.57	25.40	-11.49	-1.06	3.78	0.21	-0.19	0.26	-0.23	-0.14	-0.02

***p-value ≤ 0.001, **p-value ≤ 0.01, *p-value ≤ 0.05, ‘p-value ≤ 0.1.
The red and blue colours represent negative and positive values respectively. The numbers 7–11 indicate the months of the growing season (July to November). Provinces are listed from west to east.

Table 7
Number of months with positive and negative significant correlations at 90% and 95% significant levels.

Correlation	Significant level	Tmin	Tmax	Tave	Precipitation	SPEI1	SPEI3
Positive	≥95% (p-value ≤ 0.05)	0	0	0	2	2	3
	≥90% (p-value ≤ 0.10)	1	0	0	7	8	7
Negative	≥95% (p-value ≤ 0.05)	7	11	10	0	0	0
	≥90% (p-value ≤ 0.10)	14	15	15	2	4	0

The 90% confident intervals, which present uncertainty of the regression models in the estimation of yield impacts, show large ranges, crossing in some instances the yield impact = 0 line. These are due in part to opposing influences between temperatures and precipitation and between Tmin and Tmax as well as data uncertainty. Consequently, in some provinces it is difficult to determine a clear direction of total yield impact due to climate trends. The largest uncertainty occurs in Amnat Charoen province due to limited data availability (Fig. 4).

Estimated yield impacts due to trends in precipitation and SPEI-1 show clear directions, though varying from one province to another. In the Si Sa Ket, Yasothon, and Amnat Charoen provinces (in the east) rice yields decrease as a results of observed trends in precipitation and in SPEI-1 while in the Ub, Ro, Su and Na provinces yields increase. Yield gains tend to occur in July/August/September whereas losses occur later in the season (September/October).

Another clear result is that yield losses due to trends in SPEI-1 are larger than those due to precipitation trends. On the other hand, observed yield gains due to trends in SPEI-1 are usually smaller than those due to trends in precipitation. Therefore, the SPEI-1 is more responsive to rice yield changes, particularly when yields decrease.

5. Discussion

We show, in agreement with (Jagadish et al., 2010), that assessing yield changes using minimum and maximum temperatures separately provides less uncertainty than using average temperatures. There is evidence that Tmin and Tmax provide different effects on crop phenological development and physiological processes (Wassmann et al., 2009). Our results indicate that rice yields are more vulnerable to changes in Tmin than in Tmax, consistent with Peng et al. (2004). The result corroborates some literature (Nagarajan et al., 2010; Pathak et al., 2003; Welch et al., 2010) that higher Tmin contributes to lower rice yield. However, the physiological mechanism responsible for the negative impacts of Tmin on rice yields remains unclear (Peng et al., 2004; Wassmann et al., 2009). Higher maximum temperatures especially over 35 °C and lasting > 1 h during anthesis and flowering stages induces spikelet sterility (Yoshida et al., 1981), which finally results in yield reduction.

Our results indicate that increases in minimum and maximum temperatures generally have negative impacts on rice yield. However, in some provinces opposing impacts of nighttime (Tmin) and daytime (Tmax) in the multiple regression models in some growth stages indicate that the impacts of Tmin and Tmax on rice development and yield remain ambiguous. Ultimately, this contributes to large uncertainties in total yield impacts as also found by Welch et al. (2010). Accurately assessing effects of temperature change on crop yields is therefore difficult. Yield impacts due to changes in precipitation and *Spe*I-1 are clearer and point in the same direction with less uncertainty.

Rice yield are stronger correlated with the SPEI-1 than with precipitation and SPEI-3 (both in statistical significance and value). We conclude that, the 1-month SPEI is better capable of detecting soil moisture deficiency and crop stress in rice than precipitation and SPEI-3. We also examined the correlations between rice yields with 2-, 6-, 9- and 12-month SPEIs (Supplementary data Table S1) and the results show inferior to those between the yields and SPEI-1 and SPEI-3. The correlations with the SPEI-1 follows a similar pattern to those with precipitation (mostly positively correlated, except in September). In some provinces, the yield decreases with increases of precipitation

Table 8
Pearson's correlation coefficients between rice yield and monthly minimum temperature (Tmin), maximum temperature (Tmax), mean temperature (Tave), and precipitation for 1984–2013.

	Tmin						Tmax					
	Jul	Aug	Sep	Oct	Nov	Mean	Jul	Aug	Sep	Oct	Nov	Mean
Na	-0.35*	-0.42**	-0.06	-0.09	-0.18	-0.33*	-0.18	-0.53**	-0.41**	-0.27	-0.08	-0.42**
Bu	-0.26	-0.04	-0.09	-0.21	0.01	-0.15	-0.16	0.03	0.13	-0.17	-0.12	-0.15
Kh	-0.14	-0.10	-0.30	-0.34*	-0.30	-0.41**	-0.03	-0.22	0.09	-0.48**	-0.50**	-0.46**
Ma	-0.03	0.11	0.07	-0.18	-0.30	-0.18	-0.31*	-0.11	0.06	-0.25	-0.11	-0.23
Su	-0.01	0.10	0.01	0.03	-0.26	-0.16	-0.06	0.09	0.31	-0.05	0.02	0.07
Ro	-0.33*	0.05	-0.38**	-0.21	-0.27	-0.39**	-0.28	-0.42**	-0.03	-0.29	-0.10	-0.35*
Si	-0.10	0.13	-0.06	0.02	-0.33*	-0.24	-0.19	-0.01	0.01	-0.47**	-0.18	-0.41**
Ya	-0.22	-0.36*	-0.06	-0.07	-0.39**	-0.37**	-0.05	0.00	-0.16	-0.32*	-0.29	-0.41**
Am	-0.21	-0.11	0.22	0.16	-0.51**	-0.27	0.23	0.20	0.23	-0.18	-0.39*	-0.08
Ub	-0.33*	0.05	-0.03	0.07	0.35*	0.14	-0.38**	0.14	-0.20	0.25	0.19	0.05

	Tave						Precipitation					
	Jul	Aug	Sep	Oct	Nov	Mean	Jul	Aug	Sep	Oct	Nov	Sum
Na	-0.28	-0.54**	-0.37*	-0.26	-0.15	-0.44**	0.30*	0.03	0.33*	-0.18	-0.08	0.18
Bu	-0.23	0.01	0.04	-0.25	-0.07	-0.19	0.01	0.11	-0.28	0.26	0.06	0.04
Kh	-0.08	-0.20	-0.03	-0.49**	-0.44**	-0.50**	-0.01	0.19	-0.38*	-0.05	0.21	-0.08
Ma	-0.22	-0.01	0.08	-0.27	-0.24	-0.25	0.07	0.21	-0.30	0.06	-0.25	-0.09
Su	-0.05	0.11	0.24	-0.02	-0.13	-0.04	0.03	0.37*	-0.33*	0.14	-0.24	-0.02
Ro	-0.32*	-0.33*	-0.18	-0.31*	-0.21	-0.40**	0.35*	0.20	-0.27	0.08	-0.06	0.13
Si	-0.18	0.05	-0.02	-0.29	-0.28	-0.37*	0.02	0.23	-0.06	0.27	-0.26	0.14
Ya	-0.12	-0.12	-0.15	-0.26	-0.36**	-0.43**	-0.08	0.49**	-0.06	0.37**	-0.04	0.31*
Am	0.09	0.12	0.27	-0.04	-0.49**	-0.18	0.30	-0.05	-0.15	0.31	-0.07	0.11
Ub	-0.42**	0.13	-0.18	0.19	0.29	0.11	0.16	-0.08	0.04	-0.13	0.01	0.04

*p-value ≤ 0.10, **p-value ≤ 0.05.
The red and blue colours present the negative and positive values, respectively.

Table 9
Pearson's correlation coefficients between rice yield and 1- and 3-month SPEI for 1984–2013.

	SPEI1						SPEI3					
	Jul	Aug	Sep	Oct	Nov	Mean	Jul	Aug	Sep	Oct	Nov	Mean
Na	0.33*	0.12	0.34*	-0.03	-0.05	0.29	0.23	0.29	0.46**	0.20	0.11	0.35*
Bu	0.03	0.10	-0.32*	0.18	0.14	0.07	0.03	0.12	-0.12	0.01	-0.02	0.01
Kh	0.02	0.21	-0.38*	-0.03	0.25	0.03	-0.15	0.08	-0.05	-0.05	-0.25	-0.12
Ma	0.07	0.24	-0.33*	0.07	-0.23	-0.10	0.07	0.46**	-0.10	-0.14	-0.28	0.01
Su	0.02	0.36*	-0.34*	0.14	-0.20	-0.03	-0.14	-0.02	-0.04	0.00	-0.25	-0.15
Ro	0.35*	0.22	-0.28	0.09	-0.04	0.14	0.32*	0.37*	0.16	0.00	-0.19	0.16
Si	-0.02	0.25	0.00	0.32*	-0.17	0.17	0.38**	0.28	0.10	0.19	0.04	0.28
Ya	-0.04	0.44**	-0.04	0.41**	0.06	0.34*	-0.03	0.33*	0.18	0.29	0.13	0.25
Am	0.28	-0.04	-0.18	0.36	0.02	0.22	0.30	0.17	-0.12	-0.12	-0.03	0.04
Ub	0.18	-0.03	0.08	-0.15	0.04	0.07	0.25	0.25	0.06	-0.06	-0.02	0.15

*p-value ≤ 0.10, **p-value ≤ 0.05.

in the month September, even though the monthly precipitation is lower than crop water requirement. This is due to extremes in precipitation intensity, which according to the precipitation records obtained from the Royal Irrigation Department of Thailand could be as high as 250 mm per day. For example, on 21 Aug. 1987 at stations Ub67022 and Ub67092 the daily precipitations are 262.7 and 254.3 mm, respectively; on 9 Aug. 2001 at station Si57203 the daily precipitation is 263.4 mm and on 19 Sep. 2013 at station Su62013 the daily precipitation is 279.5 mm.

The trends of all climatic variables and SPEI-1 are predominantly increasing. In the Mun River basin, Tmax is rising faster than Tmin, unlike in China (Zhou et al., 2004) and India (Padma Kumari et al., 2007), the first and second largest rice producers, where Tmin has been increasing faster than Tmax. The upward trends in Tmin and Tmax are relatively pronounced in October and November and are more apparent in provinces in the East than in the West. The records also show that in some years, daily Tmax in October in some provinces exceeded 35 °C. If the observed trend continues in the future, the negative effect of Tmax on rice yield is likely to be more visible. The increasing trends in precipitation and SPEI-1 varied considerably. Negative impacts of precipitation on yields mostly occur in September, which is usually the wettest month. In absence of proper drainage, larger volumes of rainwater will likely negatively impact rice development.

The total yield losses due to recent climate trends over the past 30 years (1984–2013) in all provinces are rather low with large uncertainties. When considering only the sensitivity to the temperatures, the yield decreased between 2% to 10% per 1 °C increase in Tmin and Tmax. The rate is similar to the findings by Peng et al. (2004) at the International Rice Research Institute Farm in Philippines who concluded that in the dry season grain yield decreased by approximately 10% for each 1 °C increase in Tmin. The relatively low yield reduction in the Mun River Basin may be explained by the high drought tolerance of the two rice cultivars grown in the area (Bureau of Rice Research and Development (BRRD), n.d.). Additionally, it is partially due to opposing impacts of temperatures and precipitation, and in part because of opposing impacts between Tmin and Tmax. The impacts are determined by the magnitudes of both the effects and trends in temperatures and precipitation. The standardized regression coefficients (Bring, 1994) reveals that changes in precipitation have the most effect on yield change when Tmin, Tmax and precipitation equally changed by one standard deviation. However, in the Mun River Basin yield impacts are driven by trends in temperatures rather than in precipitation, consistent with recent research (Bhatt et al., 2014; Lobell et al., 2011). This is because trends in temperature are stronger than in precipitation.

Irrigation provides water to crops in months with high moisture deficit. Hence, the expectation is that in provinces with a higher rate of irrigated area (Table 1) the strength of associations of rice productions with climatic variables such as precipitation and SPEI-1 would be weaker. We observed that in the Nakhon Ratchasima province where almost 20% of paddy fields were irrigated, the relationships were not as strong as in Yasothon province (4.9% irrigated land) where the highest correlations of rice yields with precipitation and with SPEI-1 are found. However, the effect of irrigation on correlation values is not very clearly visible. For example in Nakhon Ratchasima, Buri Ram, Maha Sarakham, Surin, Roi Et, and Si Sa Ket, correlations between rice yields and SPEI-1 are comparable while the irrigated land of Nakhon Ratchasima is quite distinct from that of the rests. In the Khon Kaen province, with the least irrigated area at only 0.5%, the strength of association of rice yields with SPEI-1 was weaker than in Yasothon province. We find that in some provinces positive gains from the precipitation trends compensated for negative impacts from the temperature trends. This means that possible losses in yields due to global warming may be compensated, to some extent, by improving water deficiency through irrigation and crop water management. The role of irrigation in climate – yield relationships deserves further study.

In this study, we disregard the effect of CO_2 levels on rice yields because the year-to-year differences in CO_2 concentration is too small to produce the measurable yield changes (Lobell and Field, 2007). The rice yields increase by 1% for 20 ppm additional of CO_2 concentration (Parry et al., 2004). Consequently, since 1984, the CO_2 level increased by 55 ppm (Dlugokencky and Tans, 2017) contributing to roughly 2.8% increase in rice yield. This is three times lower than the total yield losses due to climate trends. Furthermore, Thailand has relatively low CO_2 emission rates (Olivier et al., 2016), hence we conclude that rice production suffers more from climate change than benefitting from an increase in CO_2 concentration.

6. Conclusion

One of the strengths of our study is on the selection of spatial and temporal scales. We carried out our analysis on the provincial level covering all the 10 provinces in the Mun River Basin. We showed that there

Table 10
R^2 values of the multiple linear regression models.

	Na	Bu	Kh	Ma	Su	Ro	Si	Ya	Am	Ub
Rice yields with Tmin, Tmax and Prec	0.31**	0.22*	0.37**	0.11	0.26*	0.26**	0.26**	0.33**	0.31*	0.19
Rice yields with Prec	0.11*	0.07	0.14*	0.08	0.13*	0.12*	0.07	0.13*	0.09	0.03
Rice yields with SPEI1	0.12*	0.10*	0.14*	0.11*	0.12*	0.12*	0.10*	0.16*	0.13	0.03

* p-value ≤ 0.10.
** p-value ≤ 0.05.

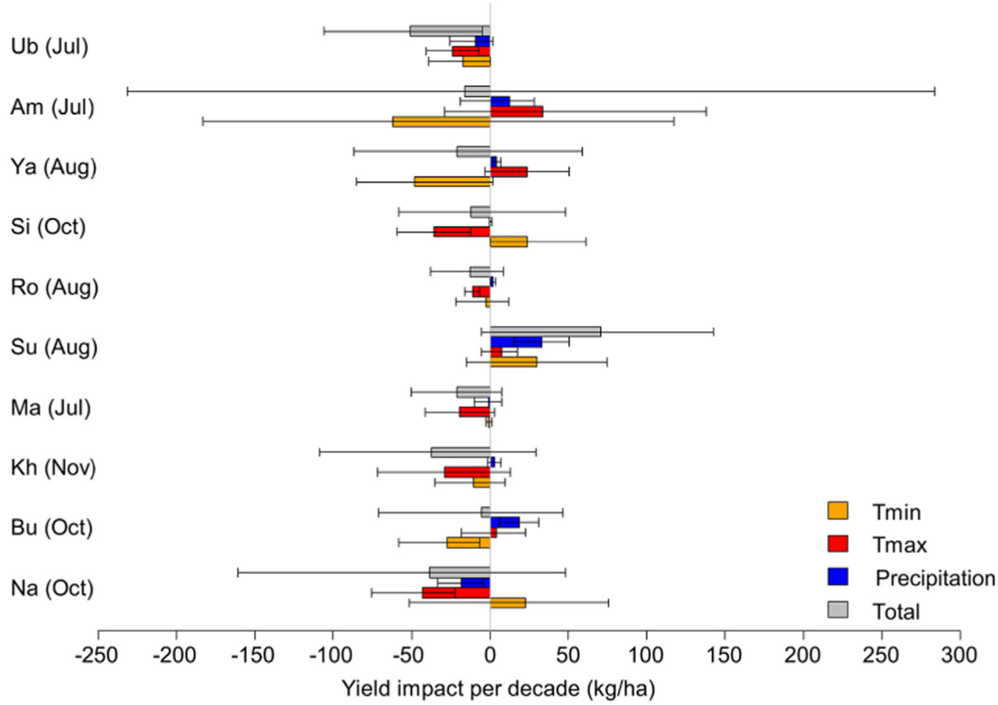

Fig. 4. Estimated impacts of climate trends from the multiple linear regression for 1984–2013 on rice yield (kg/ha/decade). Only the months with the highest R^2 for the given provinces are presented. Most other months are statistically insignificant. The orange, red, and blue bars express the yield impacts due to trends in Tmin, Tmax and precipitation, respectively. The grey bars present the total yield impacts due to trends in all climatic variables. The error bars indicate 90% confident interval.

is large variation in the impacts of climate trends on rice yields across the provinces. For example, among the months with highest correlations, rice yields have gained from the precipitation trends of the past 30 years (1984–2013) in five of the 10 provinces. While, in the other five provinces, rice yields have suffered from the precipitation trends during the same period (Fig. 5). If the analysis were limited to the basin scale, these variations would be overlooked and the results would be misleading as the gains and losses cancel out. On the temporal

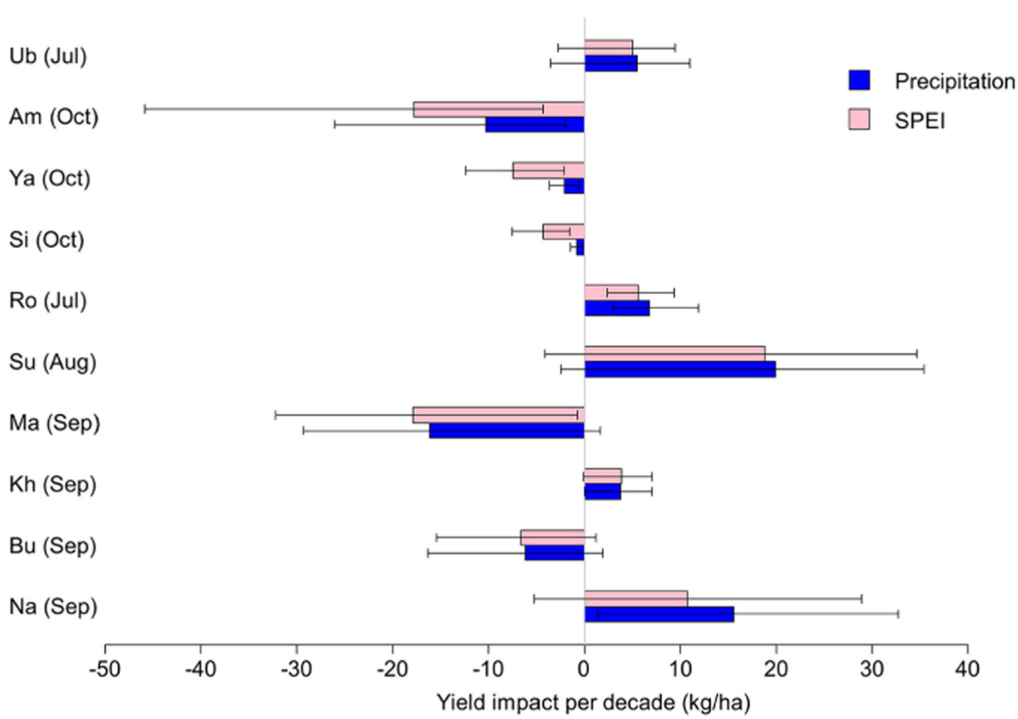

Fig. 5. Estimated impacts of precipitation and 1-month SPEI trends from simple linear regression of rice yield with precipitation and with 1-month SPEI for 1984–2013 on rice yield (kg/ha/decade). Only the months with the highest R^2 for the given provinces are presented, most other months are statistically insignificant. The blue and pink bars indicate the impacts due to trends in precipitation and 1-month SPEI, respectively. The error bars present 90% confident interval.

scale, we used the monthly time step and showed there are large variations in the degree to which rice yields are affected by the climates of different months of the growing season (Jul. to Nov.). This also allowed us to identify specific months that rice is vulnerable to changes in temperatures and precipitation. Furthermore, we find that the regression models of particular months presented higher explanatory power than that of the seasonal averages. Similarly, we also find that the multiple regression based on Tmin and Tmax separately can explain the yield variance better than Tave alone.

The SPEI-1 presented stronger correlations with rice yields than monthly precipitation and SPEI with higher aggregation periods (e.g. SPEI-3 and SPEI-6). Thus, SPEI-1 may be used as an effective tool for monitoring water stress on rice cultivation in the region. Further studies are necessary to determine the level of SPEI drought severity that should trigger a mitigation action.

Although the impact of past climate change (1984–2013) on rice yields in the Mun River Basin is still relatively low, the yield reduction is likely to be more serious in the future if the observed trends of temperatures and precipitation continue. For example, increasing trends of Tmax in October (reaching Tmax higher than 35 °C) may lead to spikelet sterility and severe yield losses. Similarly, the high precipitation intensity in month September, which is one of the major causes of low rice yields in the area, together with increasing trend of precipitation in this month may result in more severe yield losses.

The results of this study provide understanding of the significance of climate impacts on rice yields in the Mun River Basin in Thailand. The opposing impacts of Tmin and Tmax highlight the need for further research regarding effects of global warming on rice yields and its precise physiological mechanism. This study we used only climate variables as influencing factors. More insights may be obtained by including non-climatic factors, such as market prices, agronomic practices, cultivars and fertilizers, in the analysis.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2017.11.136.

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